Measuring Competence And Knowledge Using Employee Surveys: Evidence Using The British Skills Survey Of 1997

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Abstract

There have been some recent attempts to measure learning in the UK economy and to relate this to competence building systems using employee level data. There is a large array of employment data available that has been under-utilised by the innovation studies community. Thus there is a potentially useful body of data available that can be used alongside more traditional economic data and innovation surveys to provide a more complete picture of the learning economy and the role of knowledge in economic systems. The analysis presented uses the 1997 UK Skills Survey, a large scale representative survey of employees concentrating on their skills and competence building ability. Conclusions will be drawn relating to the learning economy framework and policy conclusions drawn. It can be shown, for instance, that much of the dynamism of recent times is concentrated around the use of technology, HRM practices and also more concentrated in the new service economy than in manufacturing. This has obviously important implications for policy making and competitiveness

Introduction

There has been much written in recent years about the so-called knowledge economy and whether there has been a qualitative shift in the value and impact that knowledge has on economic systems. This is by no means a new idea. For example, Machlup (1962) attempted to measure several different dimensions of the US economy in terms of its knowledge assets and knowledge production; or Arrow (1962) who introduced the concept of 'learning by doing' in economics. Moreover, no economy could function without knowledge, but there is a renewed interest into how knowledge fits into economic theory and how it can be measured (see, for example, Dosi 1996, Foray and Lundvall 1996, OECD 2000).

The argument generally goes that there have been fundamental changes in the modes and distribution of knowledge in modern capitalist economies. For example, Gibbons et al. (1994) argue that there is an increasing shift from 'Mode 1' knowledge production to 'Mode 2' knowledge. Mode 1 being characterised by a definite structure, usually discipline based, while Mode 2 knowledge is based around solving new problems which often require a multidisciplinary approach and inputs from a wider range of institutions and groups than Mode 1. The acquisition and use of knowledge more than ever before has become a crucial component of innovation systems, economic growth and progress. Mansell and Wehn (1998) argue, for example, that less developed countries are often trapped in Mode 1 systems and therefore cannot grow sufficiently.

There are at least three key reasons for this perceived shift. Two of these are raised rather frequently and another has not received so much attention. The first reason is the spread and increased performance of information and communication technologies (ICTs) and the way 'knowledge' (or perhaps more properly 'information') can now be accessed and disseminated much more readily, but of course this brings with it a whole set of problems that are not so easy to deal with. Freeman and Soete (1994) noted that the spread of ICTs would require significant processes of experimentation and learning which are still underway.

The second reason (which is not unconnected to the first) is the spread of different management practices and the reorganisation of labour processes along what might crudely be called ‘Japanese’ lines (see Gjerding, 1992, Tomlinson, forthcoming, Michie and Sheehan, 2000). This entails workers and firms reorganising the way they learn/work/communicate knowledge. As societies move from an era of Fordist mass production emphasis shifts from energy intensive to information intensive systems which require different modes of working - including lifelong learning, multi-skilled and flexible workers and flatter hierarchies within firms - to allow information and knowledge to flow more easily (see Perez and Boyer, 1991).

The third reason is the continued structural change associated with the rise of the service sector. The very nature of commodities, whether they are used as producer inputs or consumer goods, is changing fundamentally. With respect to producer inputs, the progressive outsourcing of service functions by manufacturers in the last two decades has led to more transactions between what might be called knowledge intensive business services (KIBS) - who do not produce anything tangible - and material producers. This has gone hand in hand with new services that have sprung up in the wake of this ‘outsourcing revolution’. Therefore producers increasing buy intangible ‘knowledge inputs’ such as market research, IT services and other business services (see Tomlinson, 2001a) which they may previously have produced themselves. Thus there have been fundamental changes in the production, distribution and exchange of knowledge in the production process. This gives the impression that knowledge is now a much more important input in the manufacturing process as well as in the new ‘service economy’ (see Miles and Boden, 2001).

Furthermore, with respect to consumer products, rises in disposable incomes have allowed manufactured consumer goods to become more sophisticated in the sense that consumers are now confronted with a whole bundle of complex services packaged with material products such as telephone helplines, insurance and other after sales services. Thus a material commodity is no longer essentially the crystallisation of labour and matter at one point in time which then appears on the market, but often involves the continued engagement with labour and personal knowledge at future points in time (it also requires a more sophisticated - learning? - consumer).

This temporal extension of market mechanisms has increased the 'anarchy' of production. Not only do producers often not know whether their products will sell, but they also have to promise to provide a raft of services, that may or may not be used, for significant periods of time after the material product is 'sold'. This makes the producers' lives much more complex. This as well as their products embodying knowledge that is now often outside the remit of the producing firm. The market has therefore become temporally extended and knowledge intensive for consumer products as well as intermediate inputs in the production process.

The increasing importance of learning and competence building with respect to knowledge production

In a recent paper Lundvall et al (2001: 11) state that there are now three major challenges for innovation studies:

- Focus needs to be placed on the process of learning and competence building.
- It needs a more dynamic dimension that relates to the creation, transformation and passing of innovation systems.
- A broadening of the analysis of economic development and its relations to social and ecological sustainability.

It is the first point that will remain the focus of this paper, but the other two are just as relevant. These authors prefer the term 'learning economy' to knowledge economy and characterise this new context as a speeding up of the rate of change 'giving a stronger importance to learning processes for economic performance' (ibid., p.11, see also, for instance, Lundvall and Johnson, 1994, Archibugi and Lundvall, 2001). Thus a capacity for learning is specified as one of the key characteristics of a competitive economy or innovation system. Lundvall et al. continue: 'So far, the studies of national systems of innovation have given too little emphasis to the subsystem related to human resource development. This includes the formal education and training, the labor market dynamics and the organization of knowledge creation and learning within firms and networks' (2001: 11). Lundvall has also recently extended the analysis of the learning economy to include health systems (Lundvall 2000).

As an aside this overall systemic view of knowledge creation as a process of learning set within a complex set of socio-economic, national and cultural limits reinforces the need to study what Ohkawa and Rosovsky (1973) referred to as ‘social capability’. There needs to be a general overall environment conducive to building competences within systems of innovation that will have limits placed on it by bad health systems and poor education as well as the more traditional concerns of economists such as productive investment, trade and technology. People will be able to learn faster if they are effectively educated and healthy, but these considerations receive less attention than they should in the innovation literature.

Knowledge measurement in economics

Many economists have tried to measure knowledge and knowledge flows in economic systems. For example there is a large literature on spillovers and absorptive capacity where knowledge is supposed at, say, sectoral level, to flow more or less freely between different parts of the economy and be absorbed at more or less different rates. Tomlinson (2000, 2001b) has also attempted to measure knowledge flows from knowledge intensive services using input-output tables. While this type of work has an important place in empirical economic investigations of knowledge, it suffers from at least two significant limitations. First the fact that knowledge is as hard to measure as it is to define. The usual way in the studies just mentioned is by some relation to the size of a transaction between a ‘knowledge producing sector’ and a consumer, or the amount of R&D spent, number of patents produced etc. This implicitly imposes a kind of ‘quantum theory of knowledge’ on the analysis. That is that a measurable amount of useful knowledge is transferred from seller to buyer during the transaction, say, which is proportional to the size of the transaction. In other words there is implicitly some measurable quantum or indivisible unit of knowledge.

This is further confounded by a second limitation, which is that knowledge generation is essentially a relational concept. It arises from complex interactions between human agents or between agents and technologies that can change quite rapidly. For example, a computer may be said to have a great deal of knowledge embodied in it, but it makes no difference if the user of the technology has limited capabilities. As Stan

Metcalfe has recently emphasised, only individuals can know and what they know 'depends on perceptions, introspection, memory and inference, in short, experience allied with reason (Audi, 1998)' (see Metcalfe, 2001: 568). This type of phenomenon cannot be accurately measured using the transaction approach.

This is not to say that the current empirical literature is redundant – far from it – but there needs to be a broader outlook, and a combination of different techniques and data sources is required in order to explore the complexities of knowledge and its role in innovation systems, growth and economic development. The types of analysis undertaken until now can only give a very partial account of the situation and ignore wider issues of competence building and learning in economic systems.

Measuring knowledge and learning using employment data

Is it possible to adequately measure learning and competence building? Is it possible to say which occupations and sectors of the economy are learning and therefore producing knowledge at a more rapid rate, or which stimuli can be applied to increase the rate at which people can learn, produce knowledge and increase their competences?

There have been some recent attempts to measure learning in the UK economy and to relate this to competence building systems using employee level data. There is a large array of employment data available that has been under-utilised by the innovation studies community. Tomlinson (1999) used employee level data from the Employment in Britain survey of 1992 to show that learning in the UK was taking place at a faster rate in some sectors than in others (for example, knowledge intensive services) after taking the occupational structure into account. Other investigations showed that learning is increased if employees are involved in certain HRM practices such as group working or quality circles (see Tomlinson, forthcoming). Also access to technologies such as using computers had a positive effect.

This was taken further by Tomlinson and Miles (1999), who showed using the same data that different career patterns also had an effect on a person's propensity to learn. Other work using labour market and labour mobility data has also started using employment register data in Scandinavian countries and labour force surveys in Europe (see OECD 1999, OECD 2001). This latter work attempts, among other things, to map knowledge flows by tracking the movements of skilled people or knowledge workers both within and across national borders and within and between sectors.

Thus there is a potentially useful body of data available that can be used alongside more traditional economic data and innovation surveys to provide a more complete picture of the learning economy and the role of knowledge in economic systems. A further exploration of another employee database now follows. Whereas economic studies of knowledge like those referred to above tend to use a macro or meso-economic approach, this approach uses micro data (in the sense of the individual employee, not the firm) and implicitly assumes that by aggregation one can compare different sectors and occupations in national economic systems. It is a bottom up approach rather than a top down one.

The UK Skills Survey 1997

One of the great advantages of the 1992 Employment in Britain Survey used in Tomlinson (1999) was that it asked employees directly whether they constantly learned new things in their jobs. However, this question is rarely asked in surveys. It is more usual for employment surveys to ask about skills or training. One of the problems with the analysis of the 1992 data is that it is now almost 10 years old and it was collected at the height of a serious economic downturn. The Skills Survey of 1997 is an opportunity to revisit some of the questions raised in Tomlinson (1999) with more recent data and to use different indicators of knowledge creation and learning.

The Skills Survey of employees in Britain had the following objectives and collected extensive data on these topics:

- to develop further the concept of and methodology for measuring different types of skills using an employee survey;

- to investigate the impact of various antecedents on skills, including personal characteristics and, especially, forms of education and training;
- to investigate the impact of various skills on pay;
- to investigate which skills are changing during the 1990s, and to what extent;
- to investigate how skills are distributed among the employed population and how far the pattern of skill and skill change corresponds to a learning society, and consider appropriate policy conclusions.

The data were collected from individuals aged 20-60 years old inclusive in Great Britain who were also employed at the time of interview. The number of people in the target sample was 3,676 and 2,467 interviews were obtained. (The weighted sample size is 2501 – weights were applied to all the analysis below.) 36 different dimensions of work were measured from the point of view whether they were essential to the respondent's job and, if so, how efficient the respondent was at that task. Thus a very detailed description of work tasks and learning processes can be built up from these data. The data also have the usual socio-demographic variables such as age, education, gender etc. It also has extensive data on training, group working and organisational commitment etc. so a good picture can be built up of different work practices and training regimes.

The data analysis

The analysis proceeds as follows:

1. A factor analysis of the 36 dimensions of work is undertaken, which is then used to create scores of different aspects of competence and broken down by sector and occupation. This will give a broad picture or characterisation of the knowledge structure in different parts of the economy.
2. The modelling of various dimensions of learning and knowledge creation using multivariate regression techniques to control for occupational structure and economic sector.
3. The inclusion of various other variables in the models to assess the effects of various HRM practices and access to technology on knowledge creation.

Results

1. Factor analysis

Factor analysis facilitates the reduction of a large number of variables into a smaller number of summary indicators or dimensions. The respondents in the Skills Survey were asked several questions about the importance of various job characteristics in their own employment. These were rated on a five-point scale ranging from ‘essential’ to ‘not at all important/does not apply’. Note that these questions had nothing to do with the respondent’s efficiency at the task under consideration, but merely how necessary the task was in the respondent’s job. Thus these questions give a good indication of the types of skills necessary in various sectors and occupations irrespective of whether the worker is good at them. These questions (36 in all) were used in the factor analysis. Later in the questionnaire, the interviewees were asked how efficient they were at the 36 activities (assuming they were listed as important to some extent). These latter questions are explored in the regression analysis that follows the discussion of the factors[1].

The factor analysis (in this case principle components followed by varimax rotation) produced 8 interpretable factors. The factor loadings are shown in table 1.

[1] Using the efficacy measure instead actually produced very similar results.

Table 1 **Rotated factor solution of the importance of 36 dimensions of work (Only factor loadings above ±0.4 are indicated by a + or – sign.)**

Variable	1	2	3[2]	4	5	6	7	8
Attention to detail			+					
Deal with people						+		
Giving instruction							+	+
Presentation/speeches							+	
Persuading							+	
Selling a product						+		
Counselling clients						+		
Teamwork								+
Listening								+
Physical strength		+						
Physical stamina		+						
Skill/dexterity		+						
Knowledge of equipment		+	+					
Knowledge of product						+		
Specialist knowledge			+					
Organisational knowledge								
Using computers		—						
Spotting problems			+					
Finding cause of problems			+					
Finding solution to problems			+					
Analysing complex problems			+				+	
Error checking			+					
Noticing mistakes			+					
Planning own activities	+							
Planning others' activities	+						+	
Organising own time	+							
Thinking ahead	+							
Reading information					+			
Reading short documents					+			
Reading long documents					+			
Writing short material					+			
Writing short documents					+			
Writing long documents					+		+	
Arithmetic				+				
Complex arithmetic				+				
Mathematical skills				+				

[2] The signs of the loadings on this factor have been reversed for ease of interpretation. They were originally negative, but this does not affect the validity of the interpretation that follows.

The dimensions can be characterised as follows:

1) *Planning*: this factor involves planning ones own activities as well as those of others, it also involves thinking ahead.

2) *Physical attributes*: this factor is concerned with physical strength and stamina as well as manual skill and dexterity and knowledge of equipment. It is negatively associated with using computers. This is probably associated with manual labour or manual labour with heavy equipment. People associated with this type of work understandably appear not to use computers.

3) *Problem solving*: this factor is associated with many aspects of problem solving and spotting problems. It is also associated with error checking and having knowledge of equipment as well as specialist knowledge. It is therefore probably a very broad problem oriented dimension that may pick up many different aspects of work.

4) *Mathematical skills*: this is quite straightforwardly the use of arithmetic and mathematical skills.

5) *Literacy*: this is unambiguously, like the previous factor, about reading and writing skills.

6) *Product presentation*: this appears to be about social skills with people and clients allied with product knowledge and sales and is therefore probably associated with salespersons and sales representatives.

7) *Dissemination*: this factor is related to presentations and giving speeches, or instruction and persuasion. It also appears to be associated with analysing problems, planning other peoples’ activities and written documents. Thus it probably encompasses some form of management dissemination and persuasion of personnel at a relatively high level.

8) *Teamwork*: this factor associates teamwork along with giving instructions and listening. It is probably allied with close-knit teams of people working and co-operating in the job.

The factor scores on each of these 8 dimensions were saved for each individual. These scores are standardised to have an overall mean of 0 and variance of 1. Next, in order to characterise sectors and occupations of the UK economy, the scores were broken down by an occupational code based on the first digit of the Standard Occupational Classification scheme (SOC). This scheme is summarised in table 2. The industrial classification is more difficult. There are only around 2500 employees in the sample classified by a 2 digit standard industrial classification and if we have a very fine breakdown of industries there will not be enough cases within each industry to be confident that an adequate representation of the industry and its competence base will be achieved. Thus a compromise has to be reached where there are a reasonable number of employees in each sectoral category. The results and the numbers of employees in the categories are shown in table 3.

Table 2 The 1 digit Standard Occupational Classification

SOC first digit	Occupational group	Number of cases in data
1	Managers	355
2	Professionals	255
3	Technical and Associate professionals	246
4	Administrative and clerical	413
5	Skilled trades	320
6	Personal service workers	259
7	Sales	178
8	Process/plant and machine operatives	272
9	Unskilled workers	169

Table 3 Sectoral classification and numbers of cases involved[3]

SIC Codes	Abbreviated name	No. of cases	Includes
01-19	Ag/extraction/manuf 1	149	Agriculture, extractive industries, food, textiles, leather
20-29	Manufacturing 2	234	Wood, paper, fuel, chemicals, rubber, plastic, metals
30-39	Manufacturing 3	175	Electrical and optical equipment, transport equipment, other manufacturing
40-49	Utils/construction	185	Utilities and construction
50-52	Trade	352	Wholesale and retail trade, repair
55	Hotels and catering	89	Hotels and catering
60-63	Transport	114	Air, land, sea transport
64-71	KIBS 1	205	Telecommunications, postal services, financial services, renting of equipment
72-74	KIBS 2	190	Computer services, R&D, other business services
75	Public	166	Public admin., defence, social security
80	Education	191	Education
85	Health	300	Health and social work
90-99	Social	116	Community and personal services, other services

[3] This sectoral breakdown is not ideal. It is a compromise to balance the need for sufficient numbers in each category and the limitations of the 2 digit industrial coding used. For example, it is not clear where postal services could ideally be placed and there are too few postal workers in the sample to make a self-contained category.

Fig 1 Selected factor score averages by occupational group

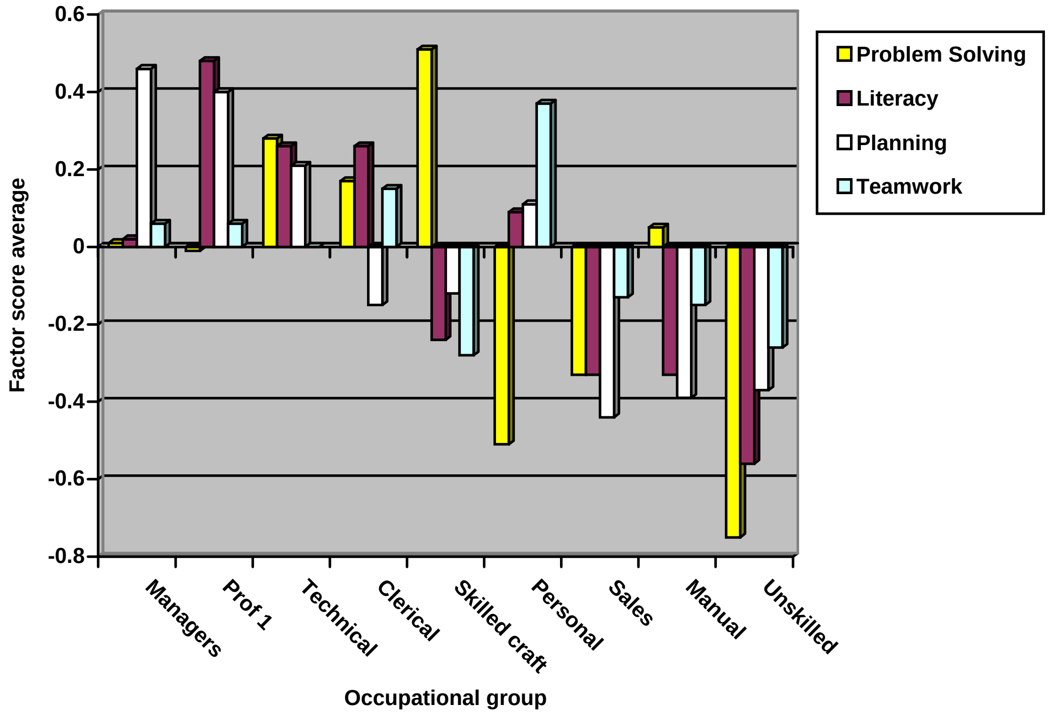
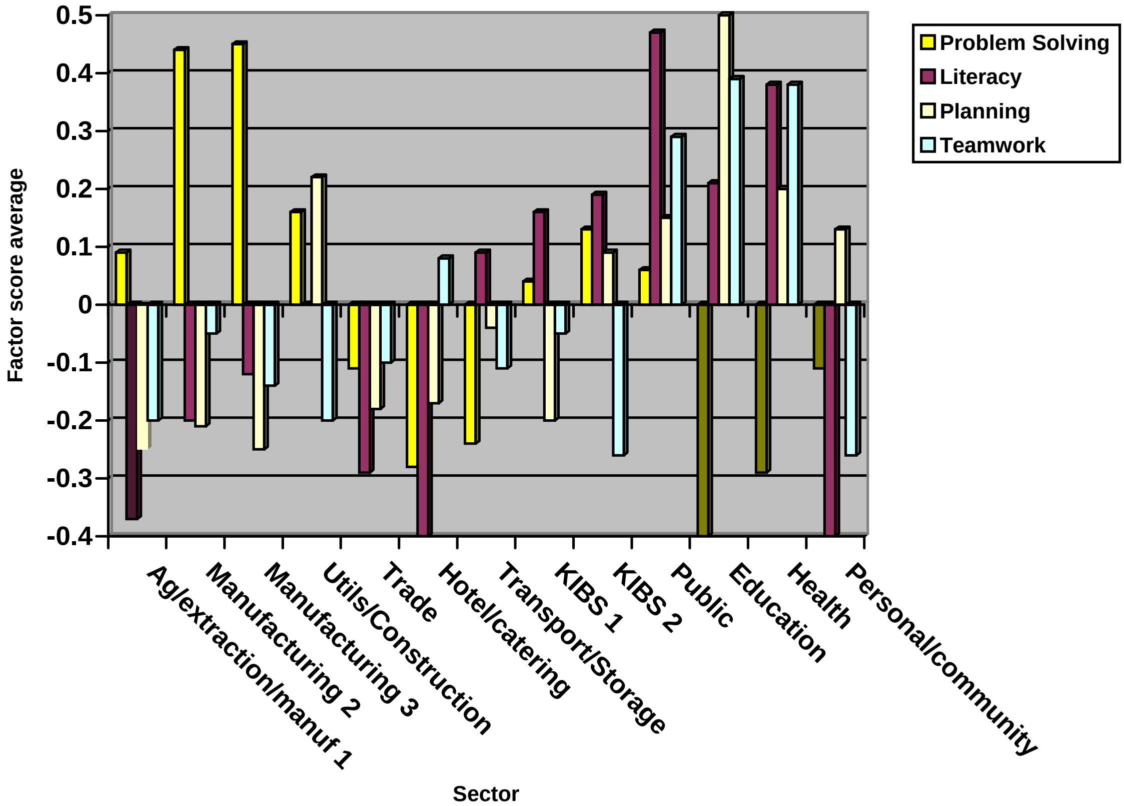


Fig 2 Selected factor score averages by sectoral groups



If the average scores on selected factors are examined by occupation and sector this gives us a characterisation of the UK economy in the late 1990s as shown in figures 1 and 2. At occupational level (fig. 1) it can be seen that the professionals score above average on literacy and planning skills, moreover technical professionals (group 3) and clerical workers (group 4) also score highly on problem solving. Managers (group 1) score highly on planning and slightly above average on teamwork, but are average when it comes to problem solving and literacy. As we move down the occupational hierarchy towards the unskilled, the scores tend to get lower on average for all 4 factors shown although group 6 (personal service workers) score quite well on literacy, planning and especially team working where they have the highest score of all occupational groups.

Turning to sectoral differences, manufacturing sectors appear to be dominated by problem solving skills while services in general seem to be dominated by literacy skills, and planning. Manufacturing sectors score below average on literacy, planning and teamwork. KIBS score higher than average on problem solving and literacy and lower than average on teamwork. KIBS2 which comprises computing, R&D services and other business services scores quite highly on planning, whereas other KIBS do not. Perhaps the surprise result here is the high performance of what are mainly public sector categories. The public administration sector itself, education and health score well above average on literacy, planning and teamwork, although the public sector and health score the lowest of all on problem solving. Thus a broad picture begins to emerge about which types of competences are associated with which sectors and occupations. Professionals and white-collar workers tend to dominate with respect to competence at occupational level, while manufacturers dominate in problem solving, and the service sectors (including the public sector) are rather strong on several other indicators.

2. Multivariate analysis of competence and learning

One of the problems with looking at factor scores or sectoral averages is that a lot of the detail is obscured. For example, sectors have different occupational structures that influence the averages and factors combine several indicators where it may be better for theoretical reasons to explore more specific aspects of knowledge and competence building. To address this we now turn to a modelling exercise where specific dimensions of competence building and learning are used as dependent variables in regression models. Using regression techniques we can control for sector and occupation as well as other dimensions of labour processes and see where, ceteris paribus, there is more or less competence building or learning taking place.

Eight dependent variables have been chosen to represent essential competence building dimensions required by the learning economy. These are shown in table 4. The first is a learning indicator, although it must be stressed that this is not the same as the learning indicator used in Tomlinson (1999) which was a direct question about having to constantly learn new things in the job. The question in the Skills Survey is prefaced by a question about training and whether the training basically includes learning while on the job. This is therefore a much narrower definition than the one used previously and not necessarily comparable. Next we have 2 problem solving variables: whether the respondent is effective at analysing complex problems and whether effective when having to find solutions to problems. Variables 4 and 5 are about knowledge dissemination. I.e. whether the respondent is effective at writing long documents (i.e. codifying knowledge) and whether they are good at teaching and passing on knowledge by other means (which is another form of diffusion of knowledge and information). Indicator 6 is the converse of indicator 4, whether the respondent is effective at absorbing information contained in long reports and documents. The last 2 indicators measure the effectiveness of generalisable or specific knowledge. Indicator 7 measures whether the skills the respondent has would be effective in another industry, and indicator 8 whether the respondent is good at using specialist knowledge. Remember that indicators 2-6 and 8 were asked only when the respondents had indicated that they were at least partially necessary in order for the respondent to do his or her job, whereas the variables used in the factor analysis measure how much the attributes are *necessary* for the job (whether the respondent is effective or not). Thus we have added a category of 'not essential' to the response. Thus the original questions are worded 'When your job involves [a specific skill/competence]… are you able to do this effectively' and the five possible answers are:

Always/Nearly always/Often/Sometimes/Hardly ever

Thus a six category dependent ordered variable has effectively been created from a 5 category variable:

0 Not necessary in the job

If necessary:

1 Hardly ever effective

2 Sometimes effective

3 Often effective

4 Nearly always effective

5 Always effective

Table 4 Questions used to derive dependent variables for analysis

	Attribute	Summary of question in survey
1	Learning by doing	Training on the job 'that is learning by example and practice while actually doing the job' in any job (yes or no)
2	Analysis	Effectiveness at analysing complex problems in depth
3	Problem solving	Effectiveness at thinking of solutions to problems
4	Codification	Effectiveness at writing long documents with correct spelling and grammar (for example, long reports, manuals articles or books).
5	Mentoring	Effectiveness at instructing, training or teaching people
6	Absorption	Effectiveness at reading long documents such as reports, manuals articles or books
7	Generalisation	How useful job skills in another industry
8	Specialisation	Effectiveness at using specialised knowledge

Indicator 1 (learning by doing) is a simple binary variable which distinguishes between those who say that they have learned on the job or not (whether this is in the respondent's current job, previous job or on some kind of training scheme). Indicator 7 is worded as follows:

'How useful would these skills [used in your job] be if you were to work for another employer in a quite different industry or service… '?

The answers are on a 5 point scale ranging from ‘Not at all useful’ to ‘Very useful’.

For the learning by doing indicator simple logistic regressions were use to predict the outcome. For the other 7 indicators ordered logistic regressions were used assuming an underlying latent dependent variable that measures the effectiveness of the measure we are trying to capture (problem solving, codification etc.).

Table 5 Results of modelling the 8 indicators against sectoral and occupational categories

	Learning	Analysis	Problem Solving	Codification	Mentoring	Absorption	Generalisation	Specialisation
Occupational groups								
Managers	0.945**	2.210**	1.564**	2.595**	1.849**	1.852**	1.800**	1.625**
Professionals	1.371**	2.373**	1.559**	3.356**	1.921**	2.327**	1.850**	1.920**
Technical	1.292**	2.202**	1.404**	2.653**	1.818**	2.070**	1.277**	1.989**
Clerical	0.906**	1.275**	0.781**	2.042**	0.968**	1.414**	1.719**	0.957**
Skilled trades	1.134**	1.570**	1.295**	1.200**	1.101**	1.212**	0.789**	1.836**
Personal serv	0.752**	1.126**	1.151**	1.388**	1.352**	1.446**	0.532**	1.632**
Sales	0.793**	0.722**	0.313	0.987**	0.515*	0.727**	0.662**	0.927**
Operatives	0.789**	0.452*	0.625**	0.732**	0.752**	0.602**	0.267	0.975**
Base Unskilled								
Sectoral								
Ag/extr/man1	0.064	-.283	-.301	-.283	-.064	-.007	0.064	-.258
Manuf 2	0.320	0.383	-.070	0.201	0.070	0.175	0.789**	-.237
Manuf 3	0.380	0.657**	0.120	0.478*	0.530*	0.693**	0.841**	0.279
Utils/constr	0.050	0.577*	0.238	0.563*	0.110	0.227	0.944**	0.286
Trade	-.209	0.179	0.122	-.071	0.265	0.312	0.758**	0.205
Hotel/cater	-.340	-.091	-.031	-.149	0.132	0.122	0.554*	-.259
Transport	0.657*	-.203	-.134	0.376	-.220	0.289	0.732**	0.162
KIBS 1	0.797**	0.455*	0.023	0.514*	0.125	0.523*	0.693**	-.010
KIBS 2	-.172	0.326	0.163	0.553*	-.057	0.309	1.007**	0.104
Public	1.293**	0.517*	0.052	0.764**	0.194	0.498*	1.005**	-.005
Education	-.192	-.019	-.207	0.335	0.548*	0.162	0.574*	-.025
Health	0.517*	-.022	-.401	0.131	-.001	0.146	0.633**	-.275
Base Personal								
Intercept 1	-1.926	0.235	-1.552	1.331	-.168	0.207	-.260	-1.301
2		0.473	-1.449	1.680	0.120	0.416	0.532	-1.040
3		0.839	-1.087	1.962	0.519	0.623	1.578	-0.613
4		1.470	-0.230	2.385	1.115	1.089	3.346	0.187
5		3.599	2.144	3.748	2.717	2.739	..	2.290
Chi	146.06**	433.58**	164.77**	679.58**	268.41**	300.14**	365.82**	213.56**
N	2467	2464	2466	2459	2458	2462	2453	2464

* significant at 5%, ** significant at 1% level.

Table 6 Results of modelling the 8 indicators against sectoral and occupational categories with technology use variables

	Learning	Analysis	Problem Solving	Codification	Mentoring	Absorption	Generalisation	Specialisation
Occupational groups								
Managers	0.304	1.397**	1.234**	1.519**	1.299**	0.986**	1.158**	1.360**
Professionals	0.622*	1.382**	1.124**	2.082**	1.237**	1.303**	1.044**	1.592**
Technical	0.602*	1.284**	1.001**	1.496**	1.228**	1.169**	0.524**	1.714**
Clerical	0.144	0.298	0.439*	0.772**	0.255	0.348	0.937**	0.654**
Skilled trades	0.827**	1.148**	1.144**	0.688**	0.860**	0.758**	0.492**	1.720**
Personal serv	0.478	0.757**	1.014**	0.880**	1.123**	1.112**	0.296	1.529**
Sales	0.340	0.270	0.164	0.323	0.135	0.182	0.308	0.782**
Operatives	0.548*	0.240	0.558**	0.352	0.582**	0.315	0.118	0.878**
Base Unskilled								
Sectoral								
Ag/extr/man1	-.013	-.487*	-.379	-.362	-.145	-.111	0.035	-.341
Manuf 2	0.143	0.051	-.257	-.145	-.146	-.121	0.650**	-.375
Manuf 3	0.128	0.264	-.076	0.033	0.276	0.381	0.623**	0.154
Utils/constr	-.067	0.468*	0.182	0.531*	0.061	0.169	0.997**	0.217
Trade	-.315	-.020	0.028	-.188	0.223	0.225	0.744**	0.151
Hotel/cater	-.392	-.105	-.019	-.132	0.096	0.172	0.621*	-.316
Transport	0.548	-.470	-.242	0.288	-.421	0.148	0.727**	0.043
KIBS 1	0.586*	0.090	-.169	0.100	-.128	0.161	0.506*	-.169
KIBS 2	-.387	-.041	-.017	0.147	-.270	0.005	0.786**	-.030
Public	1.119**	0.253	-.085	0.489*	-.007	0.246	0.855**	-.105
Education	-.375	-.180	-.289	0.169	0.422	-.064	0.458*	-.088
Health	0.529	-.025	-.411	0.218	0.010	0.179	0.756**	-.292
Base Personal								
Computerised Equipment								
Simple use	0.914**	1.119**	0.405**	1.388**	0.883**	1.311**	0.540**	0.326**
Moderate use	1.117**	1.340**	0.471**	1.958**	1.088**	1.635**	1.226**	0.383**
Complex use	0.994**	1.881**	0.864**	2.283**	1.235**	1.870**	1.147**	0.661**
Advanced	1.216**	1.832**	0.905**	2.485**	0.815**	1.384**	1.455**	0.435
Base - not important								
Intercept 1	-2.035	0.303	-1.523	1.562	-0.048	0.374	-0.215	-1.292
2		0.559	-1.419	1.948	0.330	0.603	0.593	-1.028
3		0.951	-1.062	2.269	0.673	0.824	1.679	-0.609
4		1.623	-0.195	2.741	1.285	1.331	3.506	0.194
5		3.861	2.195	4.199	2.943	3.097		2.319
Chi	215.82**	632.49**	198.74**	989.33**	385.05**	539.32**	476.38**	235.26**
N	2425	2422	2424	2417	2416	2420	2412	2422

Table 7 Results of modelling the 8 indicators against sectoral and occupational categories with HRM variables

	Learning	Analysis	Problem Solving	Codification	Mentoring	Absorption	Generalisation	Specialisation
Occupational groups								
Managers	0.617*	1.937**	1.353**	2.367**	1.562**	1.593**	1.732**	1.469**
Professionals	0.925**	2.012**	1.269**	3.046**	1.509**	1.980**	1.700**	1.710**
Technical	0.898**	1.932**	1.174**	2.419**	1.479**	1.749**	1.165**	1.885**
Clerical	0.642*	1.073**	0.596**	1.872**	0.697**	1.208**	1.628**	0.875**
Skilled trades	1.022**	1.428**	1.116**	1.102**	0.884**	1.052**	0.823**	1.781**
Personal serv	0.549*	1.008**	1.000**	1.376**	1.087**	1.261**	0.511**	1.554**
Sales	0.723*	0.662**	0.182	0.926**	0.298	0.542*	0.680**	0.920**
Operatives	0.684*	0.402*	0.526*	0.727**	0.655**	0.458*	0.312	0.909**
Base Unskilled								
Sectoral								
Ag/extr/man1	-.162	-.281	-.403	-.367	-.304	-.141	0.032	-.273
Manuf 2	-.134	0.208	-.111	-.027	-.214	0.059	0.705**	-.314
Manuf 3	0.011	0.514*	0.071	0.255	0.281	0.579*	0.739**	0.229
Utils/constr	-.119	0.615**	0.337	0.539*	0.024	0.172	0.833**	0.249
Trade	-.507	0.171	0.145	-.174	0.236	0.239	0.754**	0.162
Hotel/cater	-.517	-.107	0.081	-.295	0.263	0.138	0.464	-.153
Transport	0.399	-.277	-.194	0.233	-.278	0.202	0.690**	0.198
KIBS 1	0.359	0.302	-.032	0.362	-.155	0.365	0.535*	-.057
KIBS 2	-.321	0.306	0.203	0.514*	-.150	0.286	0.944**	0.129
Public	0.736**	0.288	-.071	0.491*	-.246	0.279	0.834**	-.102
Education	-.484	-.050	-.306	0.187	0.444	0.072	0.495*	-.062
Health	0.112	-.171	-.472*	-.088	-.300	-.023	0.454*	-.361
Base Personal								
Work based on teams:								
Little	0.445**	0.308*	0.200	0.395*	0.351*	0.381*	-.103	0.051
Some	0.429**	0.459**	0.081	0.333**	0.697**	0.361**	0.211*	-.007
All	0.570**	0.322**	0.226*	0.207	0.881**	0.436**	-.033	0.144
Quality circ.	0.322**	0.317**	0.251**	0.274**	0.346**	0.103	0.027	0.168
IIP	0.552**	0.042	-.053	0.104	0.000	0.115	0.167	-.072
Meetings	0.444**	0.301**	0.202*	0.438**	0.451**	0.338**	0.308**	0.220*
Intercept 1	-2.377	0.504	-1.500	1.612	0.262	0.445	-0.145	-1.282
2		0.738	-1.400	1.971	0.657	0.657	0.672	-1.004
3		1.114	-1.051	2.255	0.992	0.864	1.732	-0.585
4		1.766	-0.186	2.687	1.630	1.330	3.520	0.235
5		3.911	2.234	4.068	3.302	3.008		2.338
Chi	273.79	446.25**	167.37**	692.02**	414.88**	326.88**	373.01**	201.41**
N	2304	2301	2303	2297	2297	2299	2292	2301

Table 8 Results of modelling the 8 indicators against sectoral and occupational categories with COP variables

	Learning	Analysis	Problem Solving	Codification	Mentoring	Absorption	Generalisation	Specialisation
Occupational groups								
Managers	0.761**	1.900**	1.177**	2.274**	1.553**	1.508**	1.538**	1.322**
Professionals	1.184**	2.053**	1.156**	3.050**	1.609**	2.021**	1.619**	1.593**
Technical	1.154**	1.967**	1.092**	2.414**	1.626**	1.821**	1.085**	1.736**
Clerical	0.777**	1.093**	0.544**	1.873**	0.779**	1.201**	1.563**	0.772**
Skilled trades	0.994**	1.447**	1.077**	1.065**	0.886**	1.037**	0.669**	1.650**
Personal serv	0.623*	0.879**	0.847**	1.142**	1.139**	1.192**	0.338	1.408**
Sales	0.662*	0.432	-.001	0.697**	0.294	0.433	0.406	0.746**
Operatives	0.729**	0.427*	0.562**	0.716**	0.669**	0.560**	0.260	0.930**
Base Unskilled								
Sectoral								
Ag/extr/man1	0.051	-.115	-.116	-.116	-.092	0.116	0.205	-.158
Manuf 2	0.276	0.493*	0.069	0.322	-.009	0.261	0.898**	-.154
Manuf 3	0.343	0.743**	0.228	0.543*	0.438	0.748**	0.912**	0.339
Utils/constr	-.040	0.454	0.122	0.463	-.051	0.127	0.857**	0.190
Trade	-.230	0.188	0.148	-.076	0.216	0.330	0.762**	0.209
Hotel/cater	-.423	-.127	-.042	-.150	0.062	0.106	0.524*	-.285
Transport	0.637*	-.208	-.098	0.405	-.271	0.307	0.733**	0.196
KIBS 1	0.746**	0.378	-.031	0.450*	0.011	0.460*	0.639**	-.096
KIBS 2	-.199	0.344	0.192	0.581**	-.096	0.312	0.998**	0.126
Public	1.215**	0.440	-.006	0.689**	0.025	0.416	0.935**	-.037
Education	-.227	0.047	-.117	0.395	0.558*	0.162	0.566*	0.077
Health	0.430	-.077	-.458*	0.050	-.168	0.061	0.560**	-.302
Base Personal								
Experience	0.330*	0.402**	0.591**	0.342**	0.562**	0.452**	0.115	0.752**
Organisational knowledge	0.276*	0.208*	0.137	0.353**	0.543**	0.322**	0.286**	0.054
Social relations	0.544**	0.147	0.126	0.097	0.504**	0.137	0.134	-.066
Customer/client relations	0.047	0.667**	0.730**	0.771**	0.134	0.587**	0.540**	0.487**
Intercept 1	-2.805	1.194	-0.530	2.207	0.976	1.191	0.422	-0.523
2		1.439	-0.425	2.769	1.353	1.410	1.222	-0.253
3		1.814	-0.053	3.060	1.688	1.625	2.287	0.188
4		2.461	0.828	3.494	2.303	2.106	4.076	1.010
5		4.622	3.266	4.877	3.941	3.783		3.151
Chi	171.53**	508.39**	253.79**	786.67**	367.72**	377.32**	413.34**	285.29**
N	2465	2462	2464	2457	2456	2460	2452	2462

Results of the modelling exercises

The results are shown in tables 5 to 8 (for reasons of space only the coefficients and significance levels are indicated). An examination of the basic models which only control for sector and occupation (table 5) shows that as far as occupation is concerned there is a general trend towards more efficiency of as one moves up the occupational hierarchy (in the sense of having a higher probability of exhibiting a particular competence). In general the top three occupations are the most likely to be efficient on all eight measures of learning and knowledge relative to unskilled workers. The highest coefficients are usually on the two professional groups followed closely by managers.

Turning to sectoral effects, one finds that there are significant variations in efficacy in different sectors. On the learning by doing indicator, for example, some services are more efficient than manufacturers after taking occupation into account. There are significant coefficients on transport and storage, KIBS 1, public and health sectors. These include several knowledge intensive services such as financial services and telecommunications, but also include transport services and public administration. In fact the public sector comes out very well on 5 out of the 8 indicators under scrutiny (learning, analysis, codification, absorption and generalisation). Other sectors that perform well on several indicators are Manufacturing 3, which includes several high technology manufacturing sectors such as computer manufacture, electronics etc., and KIBS 1 (including telecommunications and financial services).

A simple count of the number of significant coefficients shows that the top sectors in terms of the 8 indicators and after controlling for occupational structure are: Manufacturing 3, KIBS 1, Public sector, followed by utilities and construction. In other words 3 out of the 4 top sectors in terms of these competence indicators are non-manufacturing sectors.

Some further remarks are in order. First of all that workers in all sectors except agriculture/extractive and simple manufacturing (relative to social and personal services) appear to believe that there skills are generalisable across industries, while no industry had a significant effect with respect to the specialisation indicator. This may help to explain the increases in job mobility patterns seen in recent years. People are more mobile if their skills are useful to a wide variety of employers and the evidence here points to a significant lack of sectorally specific competences and an abundance of general skills.

The impact of technology

There has been a great deal of discussion about the role of technology in improving the productivity and effectiveness of employees, although the evidence is not conclusive. The general argument goes that if access to technologies such as personal computers or internet technologies is increased it will enhance the users capabilities by such routes as increasing access to information quickly and effectively and allowing the automation of tedious routine activities, thus freeing up the user for more important tasks. Tomlinson (1999) showed that access to computerised or automated equipment increased the rate of learning new things, which tends to suggest that the former argument is true. However there is still a debate about the productivity paradox and whether the huge investments in IT have been justified by significant increases in performance. The results here (see table 6) suggest that even low-level access to computers has a great impact on all 8 indicators of competence building.

The question used to derive the indicator is ‘which of the following best describes your use of computerised equipment in your job’. Simple use involves straightforward operations such as printing invoices; moderate use includes word processing, spreadsheets and e-mail; complex use includes analysing information or using CAD or specialist packages; advanced use refers to programming level operations. The base is set at those who stated that computerised equipment was not important for their work.

The results show (table 6) that computerised equipment use is a highly significant determinant of every single competence-building indicator. Furthermore, apart from the generalisation indicator, the inclusion of these variables reduced several of the sectoral variables below the 5% level of significance. This suggests that the differences at sectoral level may be accounted for in the main by differences in the levels of access and levels of use of computerised equipment by employees. This further implies that computerisation is an essential component of competence building at several levels and across several industries. Even simple use of computerised equipment had a large impact on all 8 indicators. These results highlight the possible risks involved for firms who do not invest in technology with respect to the capabilities of their employees.

HRM practices and competence building

Tomlinson (forthcoming) argues that the impact of what have been characterised as Japanese management practices has significant effects on learning. The Skills Survey asks several questions that can act as proxies and direct indicators of modern human resource management practices in contemporary firms. The ones included in the models here (table 7) are indicators of how much work is based around teams ('a little', 'some' and 'all' versus none at all); whether the employee is part of a Quality Circle; whether the employer is a member of the Investors in People (IIP) initiative – a best practice management strategy that involves training and staff development to levels specified by the Department of Trade and Industry; and finally an indicator of the levels of communication between management and employee in the workplace: whether there are meetings held where employees can express their 'views about what is happening in the organisation'.

The results show (table 7) that the most influential variable is in fact the meeting variable, which was significant on every single measure. In other words organisations where views can be expressed tend to be the ones where competence-building parameters are more efficient. This provides evidence for Lundvall and Borrás's (1998: 93) point that in the learning economy flatter hierarchies are required in order to move information around the organisation more quickly and build competence. There is perhaps no longer much room for old style hierarchical or Fordist production systems where employees are just told what to do and never get a chance to express their problems and opinions.

Group work also appears to have several beneficial effects, although it has no impact on specialisation and, perhaps surprisingly, very little on problem solving and generalisation. Quality circles also have a significant impact on learning, analysis, problem solving, codification and mentoring, but no effect on absorption, generalisation and specialisation. Participation in the government initiative ‘Investors in People’ has a disappointingly low level of impact – appearing only to affect learning on the job. Thus it appears that there is broad agreement with other studies that HRM practices have a significant impact on capabilities and competence building within the firm. Finally the results relating to communities of practice are explored.

Communities of Practice

There has been a renewed interest recently in the communities of practice (COP) literature derived from the initial studies of Lave and Wenger (1991) and its management roots (at Xerox in the early 1990s). Knowledge generation is essentially a social process and develops in alignment with the division of labour and tends to become highly narrow and specialised à la Adam Smith. One of the problems with the division of labour and specialisation in contemporary economies may be that at certain junctures in history this specialisation comes into conflict with the dynamics of technological change (Cf. Kodama on technological fusion, 1992). So a common empirical observation in new industries such as biotechnology, photonics etc. is that PhD students are not multidisciplinary enough (see Ekeland and Tomlinson, forthcoming, Hendry 1999). The combination of disciplines required at the cutting edge is not easy to generate in our education institutions. Moreover these new industries do not (yet) have official professional bodies where shared knowledge and experience can be diffused easily. They do not even have agreed common languages.

Understanding knowledge as it is held within a COP changes the way we think about knowledge as a social process in many respects. A COP is basically a body of people with shared goals, interests and sharing common languages, with agreed methods of training and apprenticeship. This enables COP members to communicate tacit knowledge quickly between their members. For firms COPS are becoming increasingly essential, as they perceive that knowledge is becoming more crucial to hold on to. In previous times knowledge was held onto in the company by developing internal labour markets and by giving employees incentives to stay within the firm and develop the firms knowledge base. Nowadays people are more mobile. This may lead firms to notions that COPs are increasingly important. If the worker thinks he/she is a member of a COP rather than a firm then the knowledge is not always lost by the firm if the employee leaves - because someone in the loop can contact that other person as a co-member of a COP rather than as a rival from another firm and get information. Obviously it may not really be that straightforward, but this is the basic idea. This can easily be related to Alice Lam's recent work on 'extended internal labour markets' where within specific sets of firms in the same industry there is now a recognised flow of important people in a narrow set of organisations who all know each other (Lam, 2000).

There is thus a tension between individualised knowledge and communal knowledge. Can a group 'know' something that an individual can't? A group within an efficient COP perhaps has greater capabilities than a group of isolated individuals. This brings up all sorts of important issues related to learning and social capital that are under-explored in the literature. There is a lot of work going on now into 'virtual COPs' and how ICTs can enhance knowledge generation across space and between institutions, but the best work here is not going on in the innovation research community, but in computer science.

It is not easy to generate variables that represent communities of practice, however some variables in the Skills Survey begin to get at some of the issues raised by Wenger (2000). First of all we have an indicator of the importance of experience. This is a key aspect of communities of practice where experience and tacit knowledge are accumulated and often passed on through an apprentice style relationship. Second, at firm level, knowing ones way around an organisation is essential for any community to prosper. If you do not know what the person in the office next door does or what people in a different department than you know about, then you may well be less efficient in general. Social relations within the firm should also therefore be important. It is no use knowing what your neighbour does if you cannot talk to him/her about it. Finally the community extends beyond the firm to clients and customers and good relations with them should help formulate goals and assist in solving problems. Thus four dummy variables have been included: whether experience is important for your job; whether good organisational knowledge is important; whether social relations with fellow workers is important; and whether good relations with clients or customers is important. The results are shown in table 8.

These variables prove to be very significant for all the indicators of competence building. The most important being experience, organisational knowledge and client/customer relations. These variables have a significant effect on most of the eight indicators explored. Surprisingly though workplace social relations only appear to affect learning and mentoring and have no impact on the other six indicators. Thus contact with work colleagues within a workplace community appears to be mainly associated more with teaching and learning than, say, problem solving or analysis.

Conclusions

It has been shown that using a micro approach to knowledge and competence measurement using employee level data may be a useful complement to other more meso and macro oriented studies of knowledge in economics. If the sample size is large enough it is possible to aggregate up from employee level within certain sectors or occupations and compare the performance of these sectors and occupations at national level. There are several employment datasets available that have not been explored very much in this field of enquiry.

Having performed this exercise on the Skills Survey of 1997 it has been shown that certain groups of workers are well ahead in the learning and knowledge stakes using several indicators. This confirms the existence of a group of knowledge workers as was found in analysis of 1992 employee data in Tomlinson (1999). This group comprises mainly managers and professional workers. At the bottom end of the occupational ladder things are rather bleak. Thus the continuing prospect of increasing polarisation is a distinct possibility if these workers are not catered for in the learning economy.

Turning to sectoral differences, factor analysis revealed that manufacturing was predominated by advanced problem solving competences (although KIBS and the public sector also scored well here), while services were predominantly associated with literacy, planning and teamwork skills. However, it has been shown using regression models that the sectors outperforming others are mainly non-manufacturing. Only manufacturing group 3, which includes high technology sectors such as computer manufacture, electronics, optical equipment etc. showed significant gains over others. The other three sectors that performed well were KIBS 1 (which includes telecommunications and financial services), the public sector, and utilities/construction. It is interesting to note that the much maligned public sector scored above average on problem solving, literacy, planning and teamwork competences while all manufacturing groups scored below average on three of these.

The regression analysis, when it was extended to include variables besides occupation and sector, revealed several interesting phenomena. First of all the impact of computerised equipment was pervasive and affected all eight dimensions of learning and competence building in the analysis. This suggests that there are still significant gains to be made from encouraging the use of computers and other high technology equipment in the workplace. Even simple or moderate use of computers appeared to lead to significant gains in all eight competences. The inclusion of these variables also appeared to diminish the sectoral effects to a considerable degree, which implies that the sectoral differences may well be mainly associated with different levels of technological infrastructure and levels of use within sectors.

Recent studies have begun to show the impact of HRM practices on learning (Tomlinson 1999) and firm performance (Michie and Sheehan 2000, Laursen and Mahnke 2000). The regressions shown here also support the idea that certain management and workplace practices have a significant impact on learning and competence building. This is especially the case with respect to communications within the firm, quality circles, and team based working. In fact organising meetings where views can be expressed appeared to be the most effective, supporting ideas that increasing workplace democracy and flattening hierarchies is associated with improved performance.

Finally some variables were explored relating to ideas about communities of practice and it was found that building up experience and organisational knowledge was extremely important in acquiring competence. This perhaps reinforces an earlier result that found that job mobility within firms led to faster learning than job mobility between firms (Tomlinson and Miles 1999). That is those workers that move around within their organisations and accumulate knowledge of the organisation are in a better position to build up their competence and skills than those who never get to know an organisation well because they move too often between organisations. Thus it may be the case that communities of practice are most appropriate when they are functioning well within the boundaries of the firm rather than in forms such as extended internal labour markets. Although the data explored here do not have the required variables to explore this in any great detail. The surprising result in these models was the relative lack of impact of social relations with fellow workers. This only had a significant effect on two out of the eight measures whereas a community of practice approach tends to emphasise this type of effect (although good social relations with clients and customers did have a large impact). Perhaps then organisational knowledge and experience outweigh social relations within the firm in terms of competence building.

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